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Critical evaluation of methods for wind-power appraisal

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Abstract

In the literature, several methods are being used to evaluate the contribution of wind energy conversion systems in a broader power-generating system. However, not all of them guarantee accurate results.

This paper critically reviews several methods used in the literature for such reliability evaluations. There are three types of methods characterised by the details considered and the simplifications made: (1) methods using complete chronological data; measured or calculated; (2) methods using a truncated set of chronological data and (3) methods disregarding the chronology all together.

In order to test the different possible simplifications, we calculate a case study for a potential wind farm. The result of the full chronological calculation is used as a benchmark to which the results of the simplified methods can be verified. The truncated method is found to be reliable when more than the top 25% chronological values are used. The methods in which the chronology is disregarded were not found accurate because of the significant correlation between consecutive wind-speed measurements embedded in the chronological data.

We therefore conclude that the most accurate results are obtained when the full chronology of both the wind-power output and the power-generation requirement are used. Most simplifications considered with the aim to limit the amount of data needed and thus to save computation time and data-gathering effort are not really justified.

Keywords: Wind power; Fluctuating power sources; Reliability

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Contents

1. Introduction

Keeping in mind global-warming (e.g. the Kyoto protocol), finite fuel supplies and the economic reality of unstable and uncertain fuel prices, energy markets are evolving towards an increased share of renewable energy. Renewable energy, amongst other broader energetic and environmental issues, is not a pure and sole scientific issue but it also has a distinct economic, industrial, political and even social dimension. This multiinterest position often leads to a somewhat blurry or pragmatic approach in which the 'proper' scientific results or methods are not always pursued.

Because of the economic (micro versus macro), social and political dimensions of energetic and environmental issues, there are often two sides; *believers* and *non-believers*. A prime example in this regard are wind energy conversion systems, WECS. On the one extreme, the believers sometimes bluntly exchange wind turbines with conventional power; 1000 MW of wind power is considered to be equivalent to, and may replace 1000 MW of nuclear power. On the other extreme, the non-believers may dismiss wind power as completely erratic, fully unpredictable and an obstruction to the reliable exploitation of the power system; this group considers WECS simply as 'a darned nuisance'.

Apart from such common popular vulgarisations, the confrontation of believers and non-believers has also found its way to scientific publications on wind-power assessment. There, the differences are of course more subtle and they are often disguised in the form of insufficiently justified simplifications or unwarranted boundary conditions.

The scope of this paper is to give an overview, an evaluation and finally a classification of methods used to determine the actual 'value' of a wind-power system in a broader power-generating system. The 'value' of the wind-power system is assessed by looking at the impact of the use of WECS on the reliability[1] of power supply or its contribution to the expansion of the power system.

We especially focus on the inuence of using chronological wind data in reliability assessment. In some studies, this chronology is scrupulously used throughout the evaluation, whereas in others it is partly or completely disregarded. In this paper, we look at the simplifications used and verify whether or not they are valid in comparison with the 'benchmark' approach of using the full chronological data sets. The simplifications that are tested are: (1) the use of truncated data sets and (2) methods disregarding chronology.

Eventually, we want to establish which approach is correct and to which extent the simplifications may be used.

In this paper, we evaluate the impact of WECS on the overall system reliability, but the methodology can easily be extended to other intermittent generation sources such as photovoltaic energy conversion or cogeneration.

2. Definitions, terminology and evaluation criteria

2.1. An overview of general definitions used in WECS evaluation

In the evaluation of a power system with or without wind energy conversion systems (WECS), many different terms and criteria are used. Some of them are briey discussed here (for more terms or a more elaborate explanation, the authors refer to Giebel [1], Van Wijk [2], Fockens [3], Garver [4] and Billinton and Allan [5], amongst others).

The *rated power* of WECS is the installed capacity. It is the maximum power that can be generated under ideal wind conditions.

The *capacity factor* or *load factor* is the actual electric energy generation as a fraction of the electricity that could be generated at rated power over the same period of time. The load factor is often expressed in *equivalent full-load hours* representing the time the WECS would have to operate annually at rated power to reach the annual generation, e.g. a capacity factor of 30% corresponds to an equivalent full-load use of 2628 h/a.

In the reliability evaluation of power systems, stochastic reliability indices can be used. A first category, designated as the *loss-of-load* or *LOL* group, is capacity-based. The *LOLP* (P stands for *probability*) gives the probability that electricity demand, or the 'load' exceeds the available generating capacity at a given time. The *LOLE* (E stands for expectation or *expectancy*) is the expected period during which the system load is expected to exceed the available generating capacity. The LOLE is most often expressed in hours per year but can

[1]The term 'reliability' of power supply is used throughout this paper in terms of probability that demand is met by adequate supply. For conventional power plants, this is a technical reliability where plants are either available or down. For wind turbines, we use the term 'availability' in terms of occurrence of a certain wind-speed level which determines the power output of a (technically available) turbine.

also be presented as a percentage or probability by dividing through a full year of 8760 h. A second group of reliability indices includes information on the depth of the power failure. The *EUE*, or *expected unserved energy*, is the total amount of energy expected not to be supplied by the system. The EUE is sometimes referred to as the *LOEE*, *loss-of-energy expectation* or *EENS*, *expected energy not supplied*.

The *capacity credit* of a WECS is the faction of its rated power that can be considered 'equally reliable' as its conventional alternative. More precisely, the capacity credit expresses how much conventional dispatchable power can be avoided or replaced by the WECS without changing the system reliability. So, 1000 MW of wind turbines with a capacity credit of 30% can avoid a 300 MW investment in conventional power. The *effective load-carrying capability* or *ELCC* stands for the additional load that can be carried by a system including WECS (compared to that same system without the WECS) without changing the overall power-generation reliability. The ELCC and the capacity credit should lead to comparable results. The capacity credit is obtained by looking at the savings possible in the supply side where the ELCC is calculated by altering the system load.

2.2. Evaluation criteria used in this paper

2.2.1. Loss-of-load expectation, LOLE

To evaluate the reliability of the power systems, in this paper, the loss-of-load expectation LOLE is used. The LOLE is defined as follows

$$\mathrm{LOLE} = \sum_{i=1}^{n} P_i(C_i < L_i) \tag{1}$$

in which

i	index acting as time step (e.g. an hour or a day)
N	full time period (e.g. 8760 h or 365 days)
C_i	available power-generation capacity in period i
L_i	maximum electric load in period i
$P_i(\mathrm{C}_i < L_i)$	probability that maximum load exceeds available capacity in period i

The probability P_i is in fact the LOLP at time i. If the available capacity C_i is smaller than the maximum load L_i, the system will fail.

Including wind power in the LOLE formula can be achieved either on the power capacity side or on the demand side. The LOLE for systems including WECS and where its effects are included on the supply side, can then be expanded as follows

$$\mathrm{LOLE} = \sum_{i=1}^{n} P_i(C_i + W_i < L_i) \tag{2}$$

with

W_i power generation of the WECS in period i

With time steps of 1 h, this LOLE formula implicitly requires hourly wind-power output data.

2.2.2. *Effective load-carrying capability, ELCC*

In the analysis of the impact of the WECS on the overall power-system performance, the ELCC is used.

In establishing the ELCC, we use the approach used by Milligan and Parsons [14]. Two LOLE curves are drawn in which the system LOLE is plotted as function of the peak load. One LOLE curve applies to the system without additional WECS. The other LOLE curve applies to the same system in which the WECS are now implemented. The horizontal distance between both curves is the difference in peak load carried at a particular LOLE level. This distance defines the ELCC.

3. Utilisation of wind data: a literature survey

In the assessment of wind power, the most profound methods use the full chronology of both the wind data and the overall power demand. Such methods are considered to be correct and they will be used as the 'benchmark' approach in this study. In some cases, the chronological profiles are measured; in other cases, these patterns are calculated or simulated.

In many studies, short cuts, adjustments or simplifications are utilised for the evaluation of WECS. There are two main motivations to use these simplifications. On the one hand, the chronological detail of wind data may be difficult to monitor or measured data may not be available. On the other hand, the use of a considerable amount of data may lead to much computation effort or may require a lot of data storage. The simplifications discussed in this paper are based on the use of truncated data sets or on approximations disregarding chronology.

In the following sections, we give an overview of methods used in the literature. Later on, in Chapter 4, we work out a complete concrete case study in which we compare the simplified approaches to the benchmark chronological approach.

3.1. *Methods using chronological data*

3.1.1. *Use of complete measured data sets*

3.1.1.1. Description of the method. It is possible to use Eq. (2) with a complete chronological set of WECS output data and central power demand values. If the WECS are already installed, the chronological power output of such systems can be used. If power-generation data are not available, wind-speed measurements have to be used and translated into power-generation profiles by means of the output characteristics of wind turbines as shown schematically in Fig. 1.

3.1.1.2. Pros and cons. The advantage of using a full chronological set of wind-power output data is that this approach leads to correct results without simplifications or risk of misinterpretation.

One disadvantage is the amount of required data; the accuracy of the LOLE will improve if detailed wind-power output data are available. This may lead to a large amount of data, especially if WECS at many different locations are considered.

Another disadvantage is that wind-power profiles are largely unpredictable. Using one unique set of measurements may lead to biased results. Preferably, reliability computations can be performed using different sets of measurements.

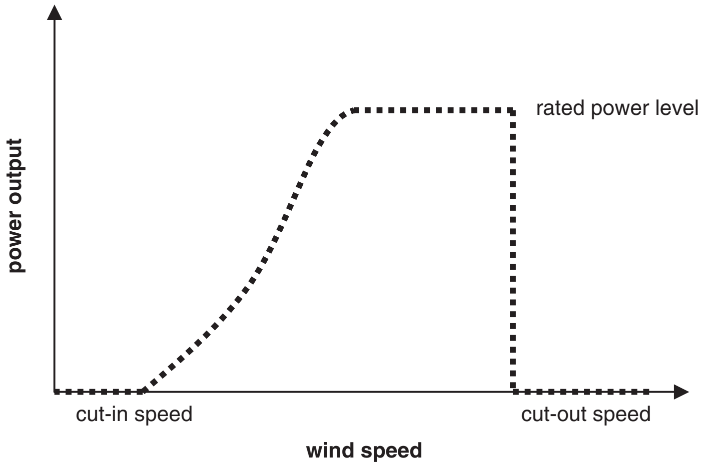

Fig. 1. Wind-turbine power output in function of wind speed.

3.1.1.3. Examples from the literature. Van Wijk [2] uses hourly wind-speed data from 11 meteorological stations in the Netherlands over a period of 10 years to calculate the capacity factor and the capacity credit of wind power in the Netherlands. Furthermore, Van Wijk [2] calculates the auto-correlation coefficients for wind-power production and the probability of power-output variations between consecutive hours. In his analysis, Van Wijk proves that the WECS power-output is strongly auto-correlated, thus showing the necessity to use chronological data.

The Irish TSO [9] uses actual power-output time series based on wind-speed measurements. They use one off-shore site with a resolution of 30 min and 18 on-shore sites with a resolution of 15 min.These data were used to compute the LOLE of power systems with and without different penetration levels of WECS with two different power-generation modelling tools. Also, the capacity credit was derived from these results.

The study also shows the yearly frequency of power uctuations within the resolution of the wind-speed data. For data of one single site, uctuations above 40% of rated power within 30 min are rare. For a combination of sites (67% on-shore and 33% off-shore), uctuations above 20% of rated power hardly occur within the 30 min resolutions.

Giebel [12,13] uses wind data from 60 meteorological stations in Europe. Twenty-five of these stations are withheld as 'promising' locations with an annual use above 2000 h/a. The resulting combined wind-power output time series is much smoother than a single time series. Giebel uses these time series to establish the capacity credit of WECS. In order to overcome the problem of single events occurring at peak load periods for the one particular wind series used, Giebel also shifts the wind-output profiles by an integral number of days to obtain new plausible wind-power output profiles.

Brower and Tennis [11] use hourly wind-output profiles to evaluate the impact of the WECS on the overall system LOLP.

Milligan [15] and Milligan and Graham [16] stress that capacity credit estimates that are based on data for one single year may not be credible because wind speeds can vary significantly from year to year. To overcome this problem, they suggest to create many different synthetic wind-speed data and recalculate the capacity credit for every case. This way, they find a distribution for the capacity credit rather than one result.

Martin and Carlin [21] prefer using data of several years because the capacity credit may dramatically vary from year to year depending on the joint variability of wind speed and the overall electrical load.

3.1.2. *Use of calculated chronological data sets*

3.1.2.1. Description of the method. In absence of measured wind profiles, realistically calculated wind profiles can be used. At best, such wind-speed simulators take into account the average expected wind speed and the correlation between consecutive sets of wind-speed data.

3.1.2.2. Pros and cons. The use of calculated wind speeds avoids the need for extensive measured data.

The drawback is that the calculated data need to be validated by means of actual measurements. Even with such a validation, it is not clear whether the calculated profile is acceptable for all locations. Even if no measurements are available at one site, the average wind speed and the auto-correlation between consecutive values are required to obtain accurate results.

3.1.2.3. Examples from the literature. Billinton et al. [18] simulate wind velocities using a wind-speed time-series model including auto-regressive and moving average parameters. Variations are obtained by using white noise. In a case study, Billinton et al. [18] use their calculated wind-speed generator to determine the LOLE of systems including WECS. Billinton and Karki [19] use a similar technique to generate hourly weather data from the monthly mean values for the simulation of the output of photovoltaic power generation.

3.1.3. *Use of truncated chronological data sets*

3.1.3.1. Description of the method. Instead of using all the wind data as described in Section 3.1.1, it is possible to restrict the number of data by only looking at the periods that are most relevant for reliability assessment. In this approach, it is assumed that the system is most likely to fail during peak load or, more generally, in the period with the lowest reserve margin.

3.1.3.2. Pros and cons. The advantage of using a well considered selection of wind data is the reduction in data use and computation effort.

A drawback is that it is not clear whether such a simplification is justified. How insignificant is the cumulated unreliability at off-peak moments?

3.1.3.3. Examples from the literature. El-Sayed [10] restricts the reliability evaluation to a LOLP calculation at the annual peak load and finds a capacity credit of about 68% for WECS with a capacity factor of only 49.5%. In the literature on capacity credit, it is quite rare that the capacity credit largely exceeds the capacity factor. It might be possible that the El-Sayed estimation is too optimistic due to the truncation procedure.

Milligan and Parsons [14] investigate the possibility of only using a selection in the calculation of the capacity credit of WECS. In this selection, they only look at the system loads with the highest risk of not meeting the load. The actual calculation of the capacity credit only using this selection is then compared to the capacity credit using the full time series. In their investigation, Milligan and Parsons use a selection ranging from 1 to 30%

of the loads with the highest risk. They recommend basing this selection on the hours with the highest LOLP rather than using the hours with the highest load. By using a selection below the top 5%, the error between the exact capacity credit and the estimated capacity credit may be large.

Bernow et al. [20] compare a truncated method that uses only the daily peak load to a complete method that uses the hourly loads for evaluating the impact of WECS on system reliability. They conclude that the daily peak load method tends to underestimate the reliability value of wind generation, particularly for systems with large penetration of wind power.

3.2. Methods disregarding wind-power output chronology based on the WECS-capacity probability table

3.2.1. Description of the method

A method that is sometimes applied to reduce the data use in the reliability evaluation is to employ the WECS capacity output–probability table instead of the actual chronological data. The WECS capacity output–probability table is drawn up by classifying the possible output of the WECS in a discrete number of output levels with a corresponding probability. The LOLE equation can then be simplified to

$$\mathrm{LOLE} = \sum_{i=1}^{n} P_i(C + W < L_i) \tag{3}$$

in which W now refers to the WECS capacity output–probability table and C to the poweravailability table.

A further simplification is the use of the load–duration curve rather than the chronological load data. Then, the LOLE calculation can be further reduced to

$$\mathrm{LOLE} = p(C + W - L < 0) \tag{4}$$

where L stands for the load–duration curve.

3.2.2. Pros and cons

The use of capacity probability tables basically limits the data use. Instead of using data for every time step (e.g. 8760 hourly values per year), one single probability table suffices.

The problem is that the correlation of the WECS power output for consecutive periods is completely lost in this approach. Indeed, if a WECS is generating 80% of rated power at a particular point in time, it is quite likely that the output will also be close to 80% the next period rather than having a 0% output. By using the capacity probability table, every time a step is evaluated from scratch thereby disregarding the output of the previous periods.

Although the use of the probability tables does indeed decrease the data use during the reliability evaluation, it has to be noted that some form of measured or estimated chronological data is still needed to draw up the probability tables. If this is the case, and computational effort is not an issue, the benefits of using the capacity output–probability table are doubtful.

3.2.3. Examples from the literature

Tripathy et al. [17] use wind-speed data to establish the capacity generation–probability table for WECS. The probability table is further used to calculate the EENS in an economical evaluation of WECS.

Apart from the simplification in using the WECS capacity probability table, Chowdhury and Koval [8] also lose the chronology of the electricity demand by using the load–duration curve. Chowdhury and Koval [8] observe that, by using their method, the use of WECS does decrease the EENS, but they argue that the impact is relatively small; the WECS contribution is in terms of energy displacement rather than reliable energy supply.

4. Utilisation of wind data: a case study

In order to evaluate the impact of the data used in the evaluation of the availability of WECS, a case study is now fully worked out. In this case study, apart from the complete chronological approach, several simplifications are made in order to chart their impact on the results. In fact, we want to investigate which assumptions or simplifications may indeed be used and which ones are inadequate.

In the case study, we calculate the LOLE of power systems including WECS using realistic data. The LOLE is further on used to establish the ELCC of the WECS.

4.1. Data used in the case studies

4.1.1. Power system

The power system used here in the evaluation of future WECS investments is the test-system shown in Table 1. It consists of base-load nuclear-power units, combined-cycle and steam-cycle units for mid load and gas turbines for peak load. The technical reliability is mentioned for all units.

4.1.2. Power demand

For the LOLE evaluation, the total electricity demand pattern for Belgium is used [6]. This demand pattern is corrected for import and export to obtain a generation profile. A typical demand pattern for one winter day is shown in Fig. 2. The evolution of the weekly maximum demand is shown in Fig. 3. The profiles shown in Figs. 2 and 3 have been scaled to a maximum of 11.7 GWh/h with total annual electric energy generation of 74.5 TWh/a.

Table 1
Power system used in outage planning test procedure

Power plant[a]	Total power (MW)	Unit power (MW)	Reliability (%)
Nuclear	5000	1000	91
CC gas	3000	300	90
Steam, coal	3000	300	94
Steam, gas	2000	200	92
GT	1000	100	89

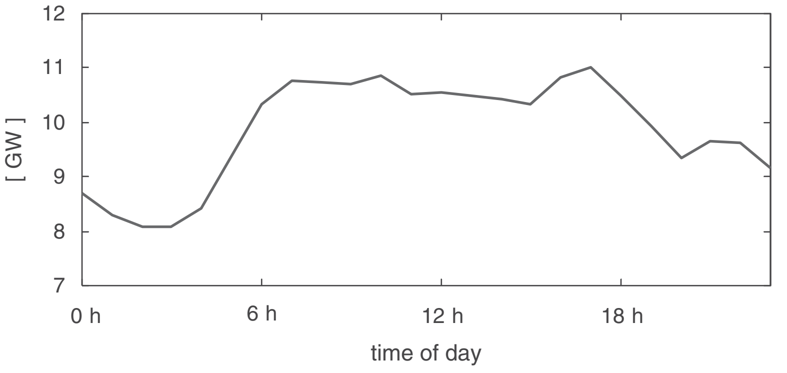

Fig. 2. Power generation pattern for a winter day.

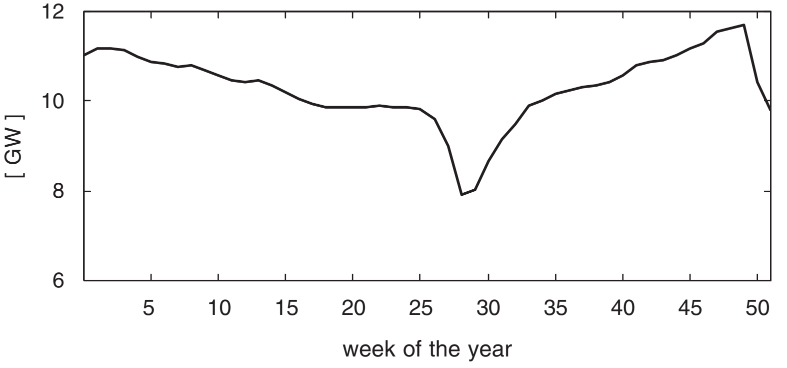

Fig. 3. Weekly maximum power demand.

4.1.3. *Wind profiles*

The profiles of the WECS are derived from actual wind-speed measurements in one near-shore location in Belgium. The WECS generation profiles have been established [7] by translating wind-speed measurements in one near-shore location in Belgium to power-generation profiles. Fig. 4 shows the normalized output of these WECS for one typical week. The capacity factor of this wind-power profile is about 33%.

4.2. *Reliability analysis of a power system including wind power*

In order to establish the reliability of a power system including WECS and the validity of the different simplifications or assumptions discussed in Section 3, the effective load-carrying capability (ELCC) of WECS is tested (ELCC according to the definition of Milligan and Parsons [14]; see Section 2.2.2). The power system, the overall generation profile and the WECS output profile are used following the options for data use discussed in Section 4.1. For our analysis, we consider 1000 MW of WECS.

Firstly, a complete chronological method is used to establish the 'correct' value for the ELCC. Then, different approximation options are tested such as the use of truncated data sets or the disregard of the chronology of wind power.

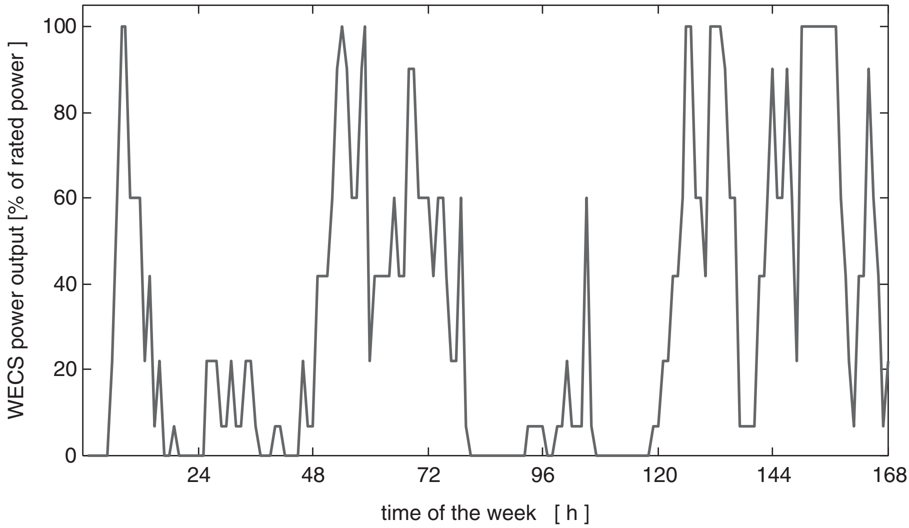

Fig. 4. Output of WECS in near-shore location in Belgium for 1 week according to Voets et al. [7].

4.2.1. Use of complete chronological data sets

In order to establish the ELCC of WECS, the LOLE of the power system with and without the WECS is compared. In a first step, we determine the capacity-outage table of the power system by calculating the probability of every possible (unscheduled) outage level (see [22] for a complete analysis of the capacity-outage tables). The resulting capacity-outage figures are schematically shown in Fig. 5. The figure on top shows the probability for every possible power-outage level. The bottom figure shows the cumulative outage probability, which gives the probability that some power level up to the value on the X-axis is affected by an outage.

The cumulative capacity-outage probability established in Fig. 5 can be used to determine the probability that the load exceeds the available capacity, i.e. P_i in Eq. (1). By calculating this probability for every hour of the year, the LOLE of Eq. (1) can be established.

The same technique is used to calculate the LOLE of the system including 1000 MW of WECS. A similar power-outage–probability table is used for the central power system in calculating Eq. (2) for the LOLE including WECS. The full chronology of the wind-power output profile is maintained.

The reliability curves of Fig. 6 show the resulting LOLE for different power generation levels by scaling the overall generation profile (a scaled version of the profiles shown in Figs. 2 and 3).

The ELCC of the WECS is calculated as the horizontal distance between the reliability curves with and without the WECS. In our case study and at a LOLE level of about 4 h per year (an order of magnitude that is also used in practice for power system dimensioning), the ELCC of 1000 MW WECS is about 280 MW or 28%.

4.2.2. Further refinement of the 'complete' reliability evaluation

There are several improvements possible to the reliability evaluation using chronological data as worked out above.

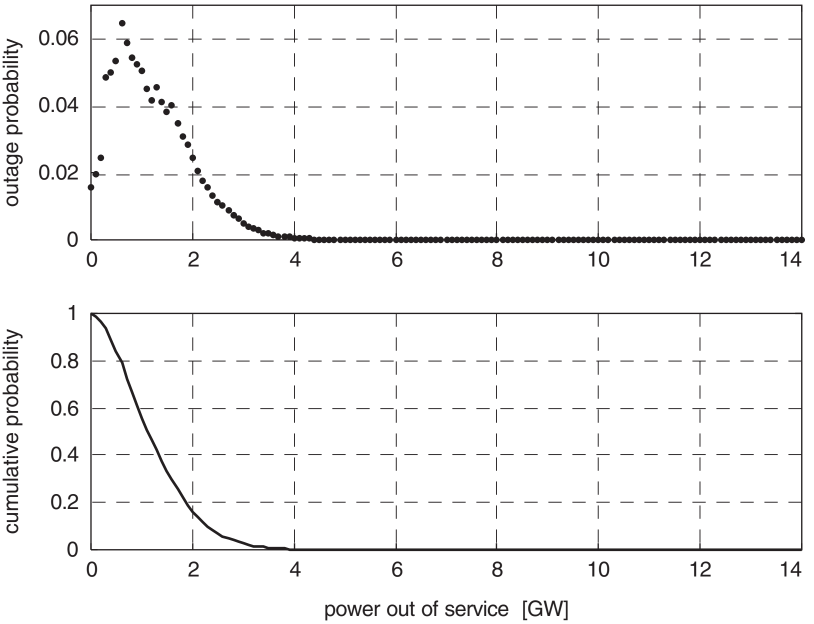

Fig. 5. Outage-probability figures for the 14 GW power system of Table 1. The figure on top shows the probability for every possible power-outage level. The bottom figure shows the corresponding cumulative outage probability.

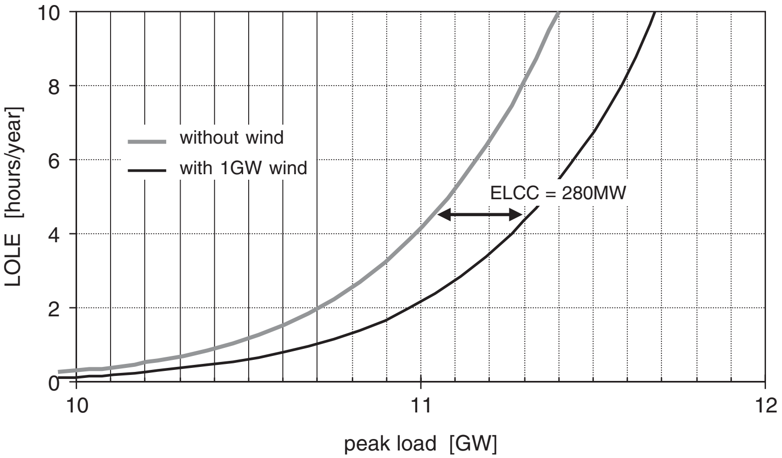

Fig. 6. Reliability curves for the power system of Table 1 with and without 1 GW of wind power expressed as the LOLE as a function of the power demand scaled to the peak load in the X-axis. The effective load-carrying capability ELCC is the horizontal distance between the two curves at a chosen LOLE level.

A first improvement would be to vary the WECS output profile to take into account the potential wind-speed variability. This can be achieved by looking at different historical measurements or to alter the profile used. To demonstrate the variability of the ELCC as a

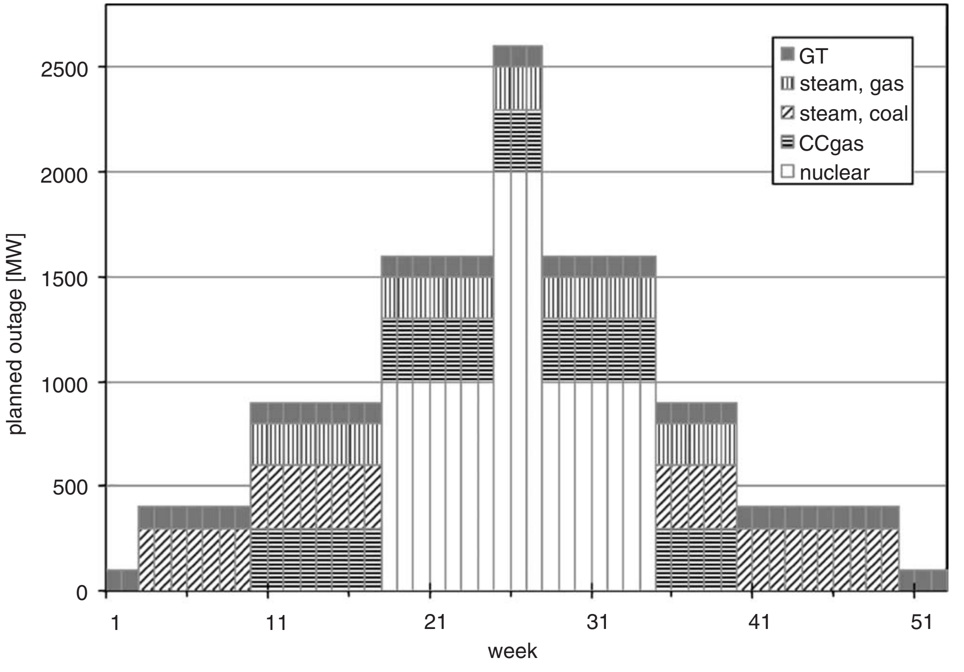

Fig. 7. A possible planned-outage scheme for the plants in the power system of Table 1.

function of the wind profile, we shifted the measured profile in time over several hours from 1 to 300 h without altering the actual time series or the annual power generation of the WECS. As a result, the ELCC varies in the range from 20 to 30%.

Another improvement would be to auto-correlate the capacity-outage table for the central power system. In the outage table shown in Fig. 5, the power outage states are independent. In reality, an outage state is correlated to the outage state of the previous hours.

A third possible improvement would be to consider the planned outage schedule of the power plants considered. Due to periodic repairs and maintenance, plants will be out of service during some period of time. Fig. 7 shows a possible planned outage schedule for the power plants in the system of Table 1. For this planned-outage schedule, the ELCC of 1000 MW WECS rises to about 310 MW or 31%. In the (actually non-realistic) case of without planned outages, the period of peak demand is dominant in the determination of the LOLE. When using the outage schedule of Fig. 7, the LOLE is dominated by the particular situation in the mid-season periods where one steam-cycle coal-fired unit and one peak unit are out of service. Other outage schedules will lead to different results. A detailed study of the impact of the outage schedule, however, goes beyond the scope of this paper.

4.2.3. Use of truncated data sets

In order to restrict the amount of data needed to perform the analysis, a truncated data set can be used. Here, we look at two possible truncation strategies; a LOLP-based truncation and a load-based truncation.

The LOLE is determined according to the LOLP of the individual hours. Therefore, it is recommended to base the truncation on the LOLP values for the separate hours as also suggested by Milligan and Parsons [14]. The problem with the LOLP-based truncation is that it does not considerably limit calculation time since the LOLP still needs to be calculated for every hour in order to be able to select the top-LOLP hours.

In contrast, an actual reduction in calculation time can be obtained by using a load-based truncation where only the highest peak loads are considered in the reliability calculation. In this case, only the LOLP for these selected peak load hours needs to be calculated.

The result of a load-based truncation in the calculation of the ELCC for our case study is shown in Fig. 8. Two cases are shown: one where the original wind time series is used and one where this wind time series is shifted over 1000 h. When more than 3000 peak loads are used, the truncated method leads to the same result as the complete approach based on all 8760 values. When using a smaller selection of peak loads, the ELCC changes considerably. When limiting the search to only a few peak loads (e.g. less than 1000), the deviation from the accurate ELCC is large, depending on single occurrences during the periods of peak load. In the case without time shift, as a coincidence, the ELCC based only on the peak load (the 'top-one' load, so to speak) is zero because the WECS do not generate power at that particular hour. For the case with a time shift of 1000 h, the ELCC based on only the top load is 47% because the WECS happens to generate about 420 MW at that time. A glance at Fig. 8 shows that there are no general conclusions on whether the truncation underestimates or overestimates the ELCC of WECS. All depends on occurrences during a limited period of time. In fact, one can only identify the appropriate number of peak loads after one has performed the computations as shown in Fig. 8. Clearly, no computation time gain will be obtained.

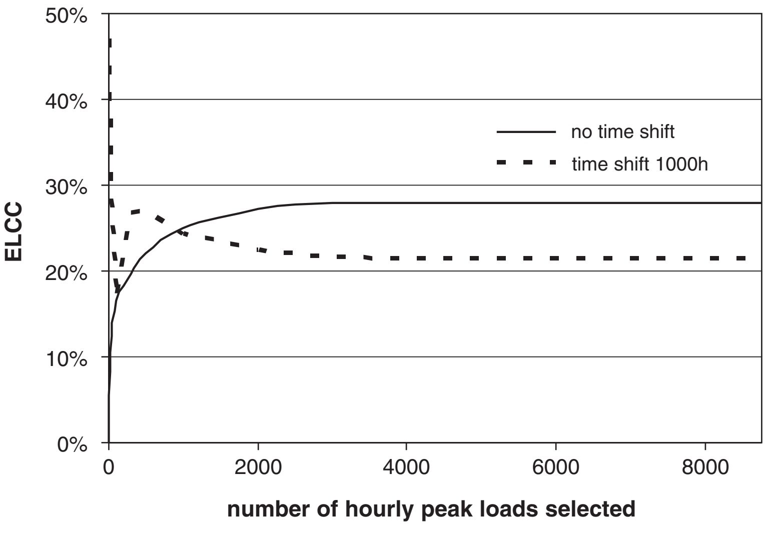

Fig. 8. Calculation of the ELCC based on a truncated data set. The values for the ELCC based on the complete chronological series are equal to 28% without time shift in the WECS time series (—) and 21% with a time shift of 1000 h (- - -), respectively. They are shown as the asymptotic horizontal parts of the curves.

4.2.4. *Disregarding chronology*

As a drastic simplification, one could completely disregard the chronology of both the wind-power data and the power demand.

The WECS time series can be replaced by the power output–probability table. For the time series used in this paper, the power output–probability table of Fig. 9 shows a 47% probability of WECS output below 20% of rated power, a 13% probability for an output between 20 and 40% and so on.

4.2.4.1. WECS-power output–probability table+chronological power demand. In a first test, we calculate the ELCC of the 1000 MW WECS by disregarding the wind-series chronology while still using the chronology of the overall power demand.

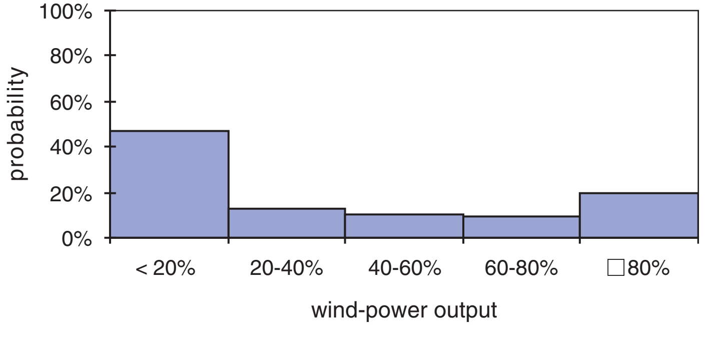

Fig. 9. Wind-power output–probability table.

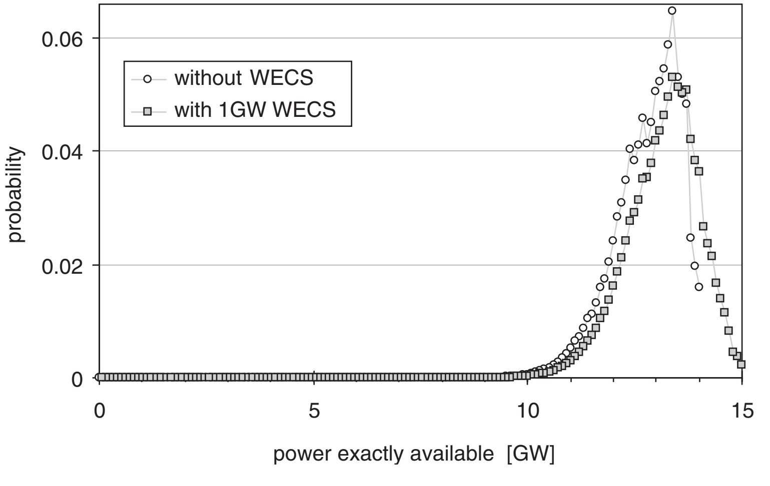

Fig. 10. Power-availability–probability function for the system with and without 1000 MW additional WECS. The curves represent the probability that the power in the X-axis is exactly available. A 'conventional' plant is considered fully available when not failing (defined by the reliability of that plant) and a WECS is available according to the wind conditions. The system without WECS has an average power available of 12.8 GW. The system also including 1 GW WECS has an average power available of 13.2 GW.

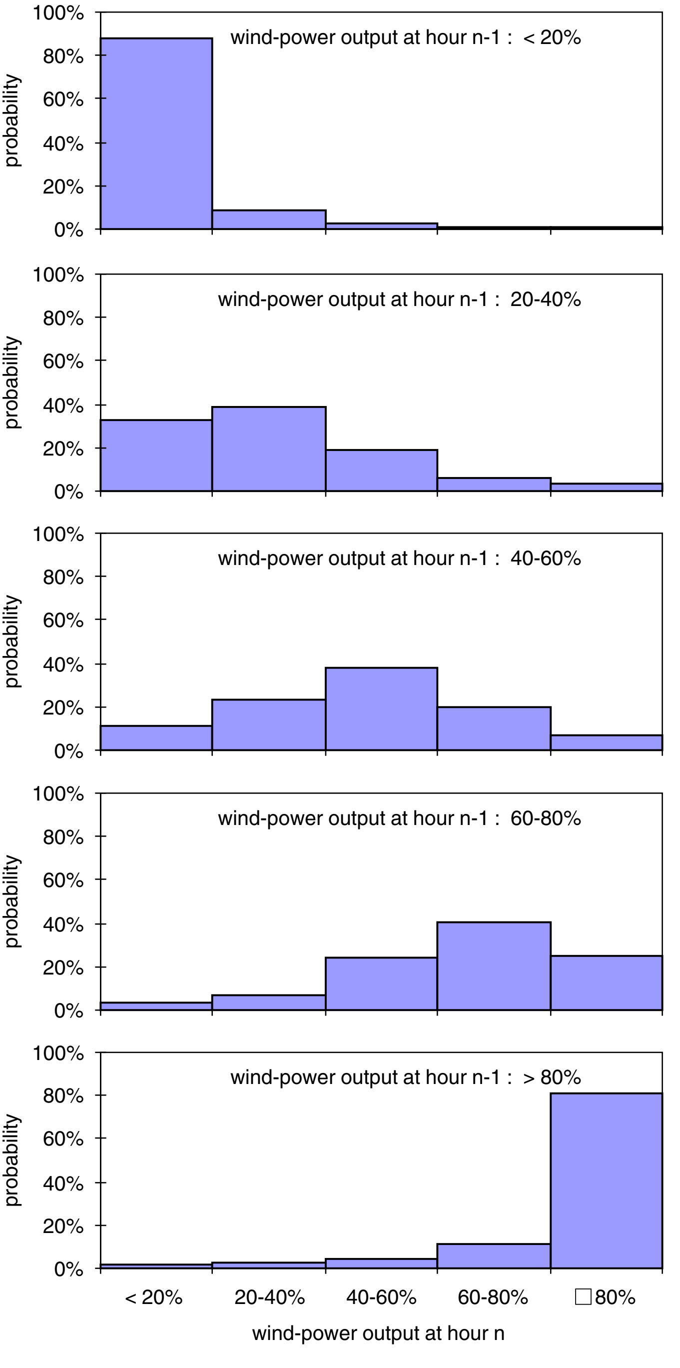

Fig. 11. Wind-power output–probability tables depending on the wind-power output of the previous hour. For a given wind-power output at hour $n-1$, each frame shows the probability of the wind-power output at hour n.

In a first step, the power-availability table for the power system with and without the WECS is constructed in Fig. 10. For the system without WECS, the power-availability figure is constructed according to the outage–probability figure in Fig. 5. For the system with 1000 MW WECS, the same figure is used in a convolution with the wind-power output–probability table of Fig. 9. As a result, the power-availability distribution for the system including WECS has a slightly higher average value (from 12.8 to 13.2 MW) and has a wider shape.

When using this combined power-availability distribution function in Eq. (3), we find an ELCC for the WECS of merely 185 MW or 18.5%, which is considerably lower than the correct value obtained from the chronological method of 280 MW of 28%.

The main reason for this error is that part of the information has been dismissed. The chronology of the wind speeds is not random, but follows a distinct pattern. The wind-power output at a particular point of time is strongly correlated with the wind-power output in a nearby time frame. This is shown in Fig. 11 where the wind-power output–probability tables are shown as a function of the wind-power output in the previous hour. These figures clearly show that it is quite likely that the WECS output is close to the output of the previous hour.

4.2.4.2. WECS-power output-probability table+load– duration curve. A further simplification is the use of the load–duration curve instead of the chronological demand curve. The load–duration curve for the demand used in this paper is shown in Fig. 12. The corresponding demand–probability curve is shown in Fig. 13.

Convolution of the demand–probability curve and the power-availability curves of Fig. 10 results in a combined probability curve from which the probability can be derived of demand being larger than available power.

This exercise is repeated for the system with and without 1 GW of WECS. The result is an ELCC of about 250 MW or 25%.

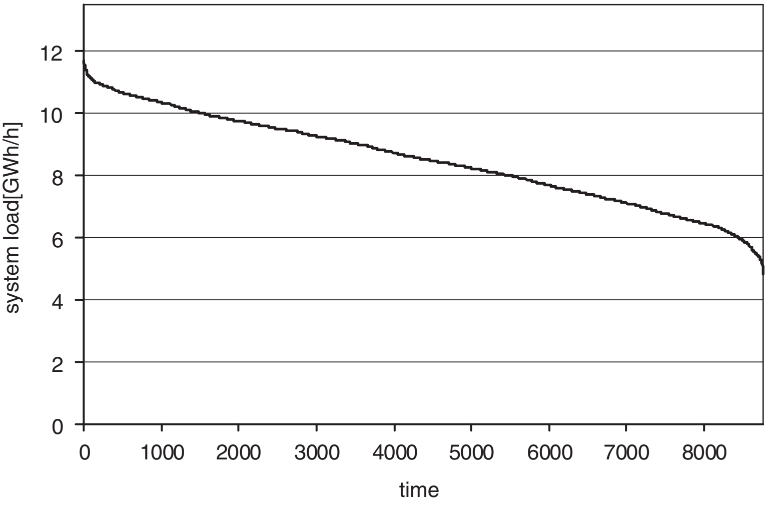

Fig. 12. Load–duration curve for power demand during 1 year (see also Figs. 2 and 3).

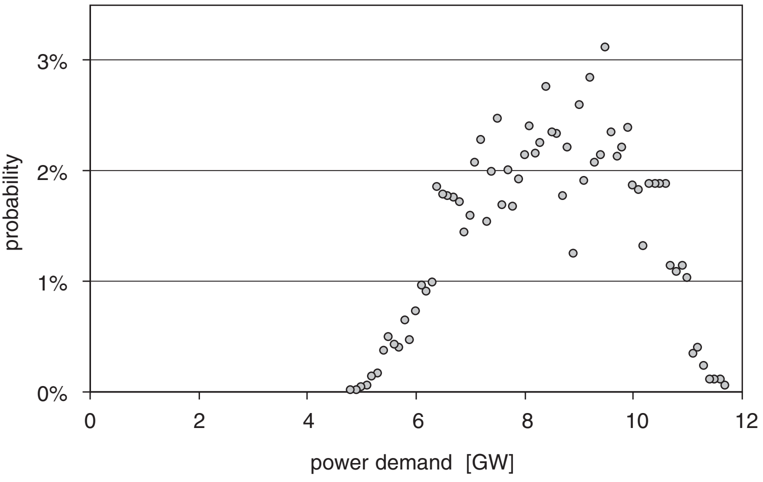

Fig. 13. Power-demand–probability curve for 1 year (see also Figs. 2 and 3).

This value is close to the value of 28% obtained from the method using the full chronology. Because of the large error already noted in the previous method whereby still chronological demand information was kept, it must be concluded that this resemblance is more a coincidence (a uke) than an overall conclusion. Indeed, the objection of losing the important and relevant wind-power chronology evidently still applies in this case.

5. Conclusions

In the literature, many methods are mentioned for the reliability evaluation of power systems including WECS.

- Some methods use the full chronology of both the wind-power output and the power demand. These methods are considered to be completely accurate. For the wind power, the chronological data can either be measured or calculated. If a calculated data set is used, calibration based on measured data is advisable.
- In order to limit the amount of data to be used in the reliability calculation, a truncated data set can be used. Preferentially, the truncation only considers those time periods in which the power system is most likely to fail; i.e. the hours with the largest LOLP. However, even in such cases, the reduction in calculation time is limited since the LOLP of all hours still needs to be calculated. Therefore, in order to really reduce calculation time, most methods based on truncation only look at the time frames with the largest demand.
- A commonly used simplification neglects the chronology of the wind-power output and/or the power demand. The wind-power output chronology is disregarded by only looking at the overall wind-power output–probability table. By using this simplification, errors occur due to two main reasons: (1) the reliability evaluation is strongly determined by single occurrences of coinciding drops in wind-power output and high overall power demand and (2) the wind-power time series are strongly auto-correlated.

In order to test the different possible methods, a case study has been carefully analysed, whereby a 1 GW WECS is imbedded in a 14 GW power system. The effective load-carrying capability, ELCC, is used to evaluate the reliability.

- For the specific data used in the case study, the complete chronological method results in an ELCC of 28%. In order to demonstrate the importance of particular occurrences in the wind profile and the power demand at the corresponding time, the measured wind series are shifted over several hours. As a result, the ELCC fluctuates in the range of 20–30%. When also taking into account a possible planned outage scheme for the power plants, the ELCC changes from 28 to 31%.
- The use of truncated data sets becomes unstable when less than the 25% highest peak loads are used. Below this point, the behaviour of the ELCC strongly depends on occurrences at those peak loads.
- Methods disregarding the chronology of the wind time series are not considered accurate. By disregarding the win power chronology, the ELCC dropped from 28 to 18.5%.

As an overall conclusion, it must be stated that the best results are obtained by using the full set of chronological data for the WECS and for the load, but taken over several years to take into account the wind variability. At best, one can save some computation effort by looking only at (more than) the 3000 highest loads (but still keeping the full WECS supply side chronology, to be able to make the selection of the 3000 top load points), rather than at all 8760 values per year.

To wrap up, the best results are obtained with full chronology; effectively all approximations lead to lower-quality results.

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